# Data-Driven Analysis of Food Corporation of India's Operations and Policy Recommendations

Arun Pa Thiagarajan*
arunp.psg@gmail.com
Indian Institute of Technology - Madras
Chennai, Tamil Nadu, India

Nehal Muthukumar*
nehalmuthu@gmail.com
Caterpillar India Engineering Solutions Private Limited
Chennai, Tamil Nadu, India

Shamshu Dharwez Saganvali
shamtcs@gmail.com
MiQ Inc
New York, United States

## ABSTRACT

The Food Corporation of India (FCI) is one of the largest supply chain management systems in Asia. The budget estimate for the FCI is Rs. 2.43 Lakh Crore [2] which is approximately 6% of India's financial budget for the year 2020-2021. In spite of such huge investments, is the ultimate aim of the FCI to build a hunger free India on track? While the FCI is enduring great stress financially, its operations are far from achieving its mandate for which it was commissioned. India stands at 116th (out of 162 countries) in achieving Zero Hunger by 2030, one of the Sustainable Development Goals from United Nations Development Program [3]. The FCI has collected and maintained key datasets since 2003 which enabled us to perform a data-driven study on its operations. This paper attempts to analyze the following questions: a)What are the main operations of the FCI and their budget allocations b) Are the Indian states/UTs utilising FCI's food grain allocations optimally and the causal factors which explains the utilisation of food grains by the states/UTs c) What could be the set of factors that determine the state and Union Territories(UT) proposal to FCI every year d) How the inference can be utilized to predict future consumption of each state/UTs. The findings provide a set of key parameters which are inputs to predictive models that predict future grain requirements for states/UTs. These parameters can further power the forecasting tool to estimate the FCI's expenditure and assist their budgetary projections for the next decade. The paper concludes with recommendations towards improving operations efficiency of the FCI for hunger free India and data sets that could be worth collecting on both state and national level by the FCI.

## CCS CONCEPTS

• **Computing methodologies** → *Modeling and simulation*; *Feature selection*.

## KEYWORDS

Data Analysis, Predictive Modelling, Regression Analysis, Food Corporation of India

**ACM Reference Format:**
Arun Pa Thiagarajan, Nehal Muthukumar, and Shamshu Dharwez Saganvali. 2021. Data-Driven Analysis of Food Corporation of India's Operations and Policy Recommendations. In *Proceedings of* . , 5 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

## 1 INTRODUCTION

The State of Food Security and Nutrition in the World [1] reported that India has the largest population of food insecure people. The estimates show that while 27.8% (42.65 crore) of India's population suffered from moderate or severe food insecurity in 2014-16, the proportion rose to 31.6% in 2017-19. In 2000, India was ranked 83 out of 113 countries and in 2019, it slipped to 102 of 117 countries in Global Hunger Index, behind its neighbours Nepal, Pakistan and Bangladesh [12] indicating that hunger problem in India is in a serious condition. These facts made us to perform a data-driven study of FCI's operations. Our main contributions helps to understand the offtake and allotment of food grains by Indian states and union territories and helps in predicting their pattern of food requirements. The results of the study have an important implication in improving the operational efficiency and better utilization of public resources by FCI. We also suggest data resources which Government of India (GoI) could collect to better manage food grain requirements.

The rest of this section is segmented as follows: a) A review of basic operations of the FCI b) How working expenses of the FCI operations are channeled. Section 2 provides specifics on the data sets used in the study, the methodology of collection and data cleaning tasks. Section 3 dives deeper into the predictive models built for the predictions of states/UTs food grains requirements and FCI's expenditures based on Minimum Support Price (MSP) of rice and wheat. Section 4 establishes the statistically correlating factors explaining utilisation of food grains by every state/UTs. Section 5 details the forecasting models built by leveraging the learning from the previous sections. The forecasts can be used for planning purposes of food grain procurement and budgetary requirements. This paper will conclude with notes on the limitations of the study, further studies which can be done and recommendations for collecting quality data sets for better forecasting.

### 1.1 Basic Operations of Food Corporation of India

The vision of the FCI is to ensure availability, accessibility and affordability of food grains to all people at all times so that no

*The work was done when the authors were students at PSG College of Technology



, ,

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

one goes hungry. The effective utilisation of food grains released by FCI has an important bearing on providing food security for the nation. The primary function of the FCI is to purchase, store, move, distribution and sell food grains. Apart from this, the FCI also ensures MSP to the farmers at the time of procurement.

The Food Corporation of India follows two kinds of procurement systems - centralized procurement system (CPS) and decentralized procurement system (DPS). In CPS, food grains procured by the states/UTs government agencies are handed over to FCI for storage and subsequent distribution in the same state or for movement of surplus stocks to other states/UTs. Under DPS, the state government procure, store and distribute the food grains within the state through the state agencies. The excess stocks procured by the state agencies are handed over to FCI in the central pool. The expenditure incurred by state agencies in both CPS and DPS are reimbursed by the Government of India (GoI) as food subsidy. To facilitate procurement of food grains from farmers, the FCI which is the nodal agency of GoI, along with various state agencies undertake procurement at purchase centres which are established at various mandis and key points.

The FCI distributes food grain to various welfare schemes running at both state level and national level at the Central Issue Price (CIP). In addition, the FCI also distributes food grains to fair-price shops. The Minimum Support Price and Central Issue Price are decided by the GoI and it is beyond control of the FCI. Using the price control schemes, GoI strives to meet twin objectives of price support to the farmers for their product as well as supply of food grains to various sections of society at a subsidized price.

### 1.2 Budgetary Requirements of the FCI

The main sources of revenue for the FCI are from sale of food grains at fair-price shops and food subsidy by GoI. The FCI incurs a top line operational loss when CIP is lesser than MSP which is reimbursed by GoI as food subsidy. For the year 2017-18, FCI incurred a food subsidy of Rs. 1, 16, 281.69 Crore and the total food subsidy released was Rs. 61, 981.69 Crore which accounts for only 53.3% of the subsidy incurred [6]. The opening balance of food subsidy for the year 2017-18 to be received stood at Rs. 81, 551.71 Crore and the closing balance was Rs. 1, 35, 933.11 Crore. To meet the budget deficit and for its various short term needs, the FCI avails both short term and long term loans, way means and advances, GoI guaranteed redeemable non-convertible bonds and equity capital subscribed by GoI. The working capital of the FCI was met by credit limits secured from a consortium of banks with a guarantee from GoI. There lies a lot of challenges, an economic opportunity and a collective responsibility to reduce the financial burden of the FCI.

## 2 DATASET CONSTRUCTION AND DESIGN

The state-level data on rice and wheat allotment and offtake for the period 2003-2019 were collected from the website of Food Corporation of India [4]. The total allotment and offtake was calculated as sum of rice allotment and offtake with wheat allotment and offtake for each state-year pair respectively. The allotment-offtake (AO) gap is the gap between allotment and offtake for each data point.

The utilisation ratio captures the extent to which allocated food grains are used by the states/UTs and it is calculated as ratio between offtake and allotment for each data point. An utilisation ratio of greater than one indicates the presence of unnatural circumstances like drought or flood due to which states might be forced to utilize comparatively more food grains than the allotment as relief materials. The over-utilization does not create operational issues as long as the FCI has maintained the minimum buffer stock mandated by GoI. Data points which has utilisation ratio greater than one or more than three standard deviation away from the mean were considered as outliers and were removed. No data point is otherwise removed as noted. Results were rounded to two decimal places.

A number of other supplementary datasets were used in the analysis. The data for the Decentralized Procurement (DCP) status of states were collected from the FCI website [5]. The data on current Gross State Domestic Product (GSDP) of the states/UTs from 2011-2019, state-wise road length and highway length from 2011-2016 and length of railway networks in a state from 2011-2017 were collected from the Handbook of India statistics compiled by Reserve Bank of India [8]. The data on population and Below Poverty Line (BPL) population of Indian states from 2011 and population projection for 2012-2036 of states were obtained from the Office of the Registrar General and Census Commissioner, GoI [9].

## 3 FACTORS INFLUENCING STATE'S PROPOSAL

In this section, we make a detailed study of factors which could explain states/UTs food grain allotments proposal to the FCI. Food grains bought by states are primarily used to feed the food insecure population and a majority of food insecure populations are below and around the poverty line and they also happen to be the largest set of beneficiaries. It is a natural choice for the population and BPL population to be a good predictor for food grain requirements of states. This leads us to the null hypothesis that *BPL population is a better predictor than overall state Population.* To validate this hypothesis, two regression models were built to find the better predictor. In both the models, the dependent variable is total allotment of food grains (rice allotment + wheat allotment) to states. In the first model, the independent variable is the population of states over the years and there were 297 data points. The first model is

$$total\_allotment = A_0 * population + A_1 \quad (1)$$

and in the second model, the independent variable is BPL population of states and there were 285 data points. The second model is

$$total\_allotment = B_0 * bpl\_population + B_1 \quad (2)$$

A key challenge in using BPL data is that the official poverty line data exist only 2011 and not available for the subsequent years. For the years 2012-19, we considered a uniform BPL change rate for all states and UTs from -1% to +3% in steps of 0.01. A BPL change rate of 0.81% (overall BPL population increases by a factor of 0.81% year over year) had the least mean squared error for equation 2. Hence, for analysis involving BPL population in the further section, we considered the same BPL change rate. The results of the models built for equation 1 and 2 are described in table 1 and 2 respectively. We observed that the model result contradicts the null hypothesis.

It was expected that BPL population to be a better estimator than overall population but it turned out the other way. This result has a significant implication because people falling near BPL category are more prone to hunger than the rest of the population and hence, BPL population should explain better than population of state. People under BPL are also more likely to consume food grains from fair price shops. This suggests two possible hypotheses - 1) states and union territories are not well targeting food insecure population 2) BPL estimates are miscalculated. We discuss the implications of the former point here and latter point in further sections and data recommendation.

For the period 2010-2019, average food grain distributed as subsidy by the FCI is 6.5 Crore MT. Assuming a constant 300 million BPL population over these years, every individual should have been benefited with 18.06 kg of food grains per month. This suggests that the states and union territories have not well-targeted food insecure population groups and benefits to the BPL population. It is to be noted that the Rangarajan Committee 363 million people were below poverty line in 2011-12 [10].

The first low hanging fruit to improve hunger index scores and reduce budgetary strain for the FCI is to better target the food insecure population. The states and union territories tend to overestimate the required food grains to reduce the type-1 error of missing food insecure population. Though overestimation is a potential issue that is to be addressed, the states/UTs should focus and invest heavily on utilising the allotted grains and distribute them to their beneficiaries periodically.

## 4 UTILISATION OF ALLOTTED FOOD GRAINS

The previous section focused on how the states and union territories can make better data oriented proposals. In this section, an analysis of state-level utilisation ratio and causal factors which might be responsible for low utilisation ratio is done. A state is under-utilizing food grains when it offtake is less than 70% of the allotment and over-utilizing food grains when offtake is greater than allotment. The efficient utilisation of food grains bears importance on reduction of poverty in the nation.

A wide range of explanatory variables like road density, length of road, railway length, density of railway network, GSDP of a state, the year in which DPS procurement is introduced were considered to explain utilisation ratio. It is intuitive that better district and village road infrastructure is required to deliver the last-mile service to the beneficiaries at the Public Distribution System (PDS) centres. The state highways are critical to the movement of food grains between district hubs. Similarly, railways are important to the inter-state transport of food grains. The Gross State Domestic Product (GSDP) is a proxy for the infrastructure in the state. The Gross State Domestic Product had a weak positive correlation coefficient with the utilisation ratio. However, the other variable holds comparatively lesser significance. A better infrastructure helps in efficient storage of food grains and distribution of food grains and this explains why states with better GSDP where able to utilize food grains better.

As discussed earlier, the FCI follows two kinds of procurement systems - centralized procurement system (CPS) and decentralized procurement system (DPS). A two sample t-test was performed to test the hypothesis that *DPS following states have better utilisation ratio than states following CPS*. We saw a significant difference in the utilisation ratio between the two systems (t-value = 4.453, $P < 0.001$). The States/UTs with DPS are able to utilise the allotted grains better than the states/UTs with CPS. For the states/UTs following the DPS system, there will be lesser steps involved in reaching the end consumer since the food grains are internally managed by state agencies and this enables quicker movement of food grains and less wastage.

To summarize the learning from the previous sections, the under-utilization of food grains by states adds to financial stress of the FCI and on the other hand, the food insecurity has become even more alarming across the country. There are several factors that can contribute to better management of allocated food grains by the states/UTs. Motivated by these learning, a forecasting model was built to predict future food grain and financial requirements of the FCI.

## 5 FORECASTING FCI'S FUTURE REQUIREMENT OF FOOD GRAINS AND BUDGET

For predicting future rice and wheat requirement of a state, we built predictive models using population and BPL population as independent variables. Along with these variable, a state/UT's proportion of rice or wheat consumed were also influential factors in estimating future requirements. The percentage of rice or wheat allotment in total allotment is taken as a proxy for the proportion of population consuming rice or wheat. The model uses the moving average of rice or wheat proportions of the previous three years since, for prediction, the current year's rice or wheat proportion will not be available. The model built for rice allotment is

$$rice\_allotment = C_0 population + C_1 bpl\_population + C_2 rice\_moving\_perc + C_3 \quad (3)$$

There were 279 data points over the years 2011 - 2019 input for the rice allotment model. The model used for wheat allotment is

$$wheat\_allotment = D_0 population + D_1 bpl\_population + D_2 wheat\_moving\_perc + D_3 \quad (4)$$

There were 280 data points over the years 2011 - 2019 input for the wheat allotment model. The results of the model built for equation 3 and 4 are described in table 3 and 4 respectively. The models built, data used and future forecast are also made public[1].

From the forecasting of future food grain requirements in the previous part, for forecasting the cost of procurement we used the Minimum Support Price (MSP) of the food grains. The MSP for paddy for the year 2020-2021 stood at Rs. 1868 per quintal and for wheat the minimum support price is Rs. 1925 per quintal [7]. The tool built allows the user to set the percentage increase in MSP price over the years as well as the change in population to predict food grain requirements and estimating the FCI's expenditures for the grain procurement. The tool also allows the user to see forecast over the next 15 years for varying below poverty line population change rates.

[1] Analysis and forecasts are available at the demo page https://github.com/arunppsg/fci-demo/

## 6 CONCLUSION

In this paper, the factors that explain low utilization of food grains by Indian states/UTs and predictive models which could help the FCI to make future forecasts and planning are developed. The predictive models that are built to find future requirements of food grains suggest that population, BPL population along with proportion of rice or wheat can be good predictors. One of the strongest recommendations is to collect BPL population data and monitor food insecure population and localities more frequently. The other variables considered for our future work includes the number of ration cards by state, grain utilization data by districts, etc.

Good policy making needs good quality data. An overall lack of robust data system hamstrings critical studies related to operations of the Food Corporation of India. Collecting granular data at each stage of the FCI process - from procurement to consumption will be helpful to conduct deeper studies. After a series of economic changes and shocks in the form of pandemic, more people would have been pushed back into the poverty line and become food insecure [11]. It becomes more imperative to collect and maintain granular data on food insecure population groups in every state/UTs to serve the beneficiaries appropriately. It is the primary role of the state, district and local government bodies to collect individual household level data to find food insecure populations and act on subsequent policy making. This will lead to evidence based policy making rather than universal policies which are fiscally stressful.

The analysis showed that states with better transport infrastructure and GSDP utilize allocated food grains better. Much work needs to be done to get a deeper understanding of why they consume better. Detailed studies are needed to determine the impact of better warehouses and godowns on the states/UTs utilization. Fair-price shops which are not functioning or at inaccessible locations might also explain the low consumption of food grains in the state.

The current implementation of PDS and Targeted Public Distribution System (TPDS) is comparatively simple since the population estimates are assumed to be static. This facilitates operationally simple frameworks for storage and logistics. With the implementation of One Nation One Ration Card scheme, the underlying assumption is that the population can migrate across states for work and livelihood and still be a beneficiary of the PDS/TPDS system. However, the lack of data on migratory population who are also food insecure will impact states proposals for all food schemes. This might also lead the states/UTs to make an even higher estimation of food grains required and ultimately wastage of economic resources. Developing a robust migration database can help the state and local bodies to understand the patterns of the floating population and this will largely help in precisely targeting welfare schemes and calculate better estimates of food grain requirements. Further granular study can be done by analyzing scheme wise requirement and utilisation of food grains by the states/UTs. The use of smart cards and Aadhar cards at fair-price shops is a great step in that direction.

It is to be understood that achieving the zero-hunger goal is a collective responsibility of the entire nation. The authors strongly believe that India can steadily progress on sustainable development goals agreed at the UN to build a better future for all. The tool like what we have developed is a small step in the direction to solve the mammoth challenge. This study is expected to provide its minimum contribution towards that goal and the mistakes are owned by the authors alone.

## REFERENCES


[1] The Hindu. 2020. More Evidence of India's Food Insecurity. Retrieved August 24, 2020 from https://www.thehindu.com/opinion/lead/more-evidence-of-indias-food-insecurity/article32424037.ece

[2] The Hindu. 2021. Union Budget 2021 | Food subsidy budget set at almost Rs. 2.43 lakh crore. Retrieved August 15, 2021 from https://www.thehindu.com/business/budget/union-budget-2021-food-subsidy-budget-set-at-almost-243-lakh-crore/article33719802.ece

[3] United Nations. 2020. The Sustainable Development Goals Report 2020. Retrieved August 15, 2021 from https://unstats.un.org/sdgs/report/2020/

[4] Food Corporation of India. 2020. Allotment and Offtake under All schemes. Retrieved July 14, 2020 from https://fci.gov.in/sales.php?view=36

[5] Food Corporation of India. 2020. Decentralized Procurement Status for States. Retrieved July 14, 2020 from https://fci.gov.in/procurements.php?view=86

[6] Food Corporation of India. 2020. Food Subsidy Released to FCI and Incurred by FCI. Retrieved August 14, 2021 from https://fci.gov.in/finances.php?view=22

[7] Food Corporation of India. 2020. Minimum Support Price of Paddy, Wheat and Coarsegrain. Retrieved August 14, 2020 from https://fci.gov.in/procurements.php?view=89

[8] Reserve Bank of India. 2020. RBI Handbook of Indian Statistics. Retrieved July 14, 2020 from https://m.rbi.org.in/scripts/AnnualPublications.aspx?head=Handbook+of+Statistics+on+Indian+States

[9] Office of the Registrar General and India Census Commissioner. 2020. Census of India. Retrieved July 14, 2020 from https://censusindia.gov.in/

[10] Government of India Press Information Bureau. 2014. Rangarajan Report on Poverty. Retrieved August 14, 2020 from https://pib.gov.in/newsite/printrelease.aspx?relid=108291

[11] Scroll.in. 2020. Hunger and malnutrition loom large over India as anganwadis stay shut amid coronavirus pandemic. Retrieved July 14, 2020 from https://scroll.in/article/972732/hunger-and-malnutrition-loom-large-over-india-as-anganwadis-stay-shut-amid-coronavirus-pandemic%20-%20hunger%20index

[12] Concern Worldwide and Welthungerhilfe. 2020. Global Hunger Index Report. Retrieved August 10, 2020 from https://www.globalhungerindex.org/ranking.html


## A TABLES

**Table 1: Total Allotment Prediction using Population**

| | | | | | | |
|---|---|---|---|---|---|---|
| **Dep. Variable:** | allotment | | **R-squared:** | 0.949 | | |
| **No. Observations:** | 297 | | **AIC:** | 4361. | | |
| **Df Residuals:** | 295 | | **Df Model:** | 1 | | |
| | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
| **const** | 88.8738 | 28.649 | 3.102 | 0.002 | 32.492 | 145.256 |
| **population** | 4.823e-05 | 6.54e-07 | 73.722 | 0.000 | 4.69e-05 | 4.95e-05 |

**Table 2: Total Allotment Prediction using BPL Population**

| | | | | | | |
|---|---|---|---|---|---|---|
| **Dep. Variable:** | allotment | | **R-squared:** | 0.809 | | |
| **No. Observations:** | 285 | | **AIC:** | 4568. | | |
| **Df Residuals:** | 283 | | **Df Model:** | 1 | | |
| | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
| **const** | 332.2602 | 53.966 | 6.157 | 0.000 | 226.035 | 438.485 |
| **bpl_population** | 0.0002 | 4.84e-06 | 34.660 | 0.000 | 0.000 | 0.000 |

**Table 3: Rice Allotment Prediction Model**

| | | | | | | |
|---|---|---|---|---|---|---|
| **Dep. Variable:** | rice_allotment | | **R-squared:** | 0.768 | | |
| **No. Observations:** | 279 | | **AIC:** | 4203. | | |
| **Df Residuals:** | 275 | | **Df Model:** | 3 | | |
| | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
| **const** | -801.3456 | 76.499 | -10.475 | 0.000 | -951.944 | -650.747 |
| **population** | 1.807e-05 | 2.49e-06 | 7.253 | 0.000 | 1.32e-05 | 2.3e-05 |
| **bpl_population** | 3.11e-05 | 9.35e-06 | 3.328 | 0.001 | 1.27e-05 | 4.95e-05 |
| **rice_moving_perc** | 1414.5578 | 101.851 | 13.888 | 0.000 | 1214.051 | 1615.065 |

**Table 4: Wheat Allotment Prediction Model**

| | | | | | | |
|---|---|---|---|---|---|---|
| **Dep. Variable:** | wheat_allotment | | **R-squared:** | 0.818 | | |
| **No. Observations:** | 280 | | **AIC:** | 4154. | | |
| **Df Residuals:** | 276 | | **Df Model:** | 3 | | |
| | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
| **const** | -443.3584 | 42.406 | -10.455 | 0.000 | -526.839 | -359.877 |
| **population** | 1.804e-05 | 2.04e-06 | 8.847 | 0.000 | 1.4e-05 | 2.21e-05 |
| **bpl_population** | 1.268e-05 | 7.74e-06 | 1.638 | 0.103 | -2.56e-06 | 2.79e-05 |
| **wheat_moving_perc** | 1243.5287 | 86.888 | 14.312 | 0.000 | 1072.481 | 1414.576 |